What is Meaningful Work?*

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Abstract

Many people derive a sense of impact or purpose from their jobs – they consider work to be a source of *meaning*. But what makes work meaningful? Theoretical models suggest that meaning can be created through social and non-social impact. We exploit rich panel data representative of workers in the United States to empirically assess these models, and estimate a non-linear production function for work meaning that allows for noisy and complementary inputs. The model explains most of the variation in meaning *between* and half of the variation in meaning *within* individuals. We find that social impact is the most effective pathway to meaning, and estimate a direct output elasticity with respect to work meaning of about 0.44. The effectiveness of non-social impact differs significantly across demographic groups. We also find evidence of a negative interaction between social- and non-social impact. A standard deviation increase in social impact is twice as effective in creating meaning for individuals that perceive their jobs as having little non-social impact, compared to those with high perceived non-social impact.

Keywords: work meaning, production function, latent factor model

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1 Introduction

Many people derive a sense of impact and purpose from their job – they consider work to be a source of *meaning*. A substantial body of work spanning organizational psychology, sociology, and economics studies the importance of work meaning, see Rosso et al. (2010), Martela and Riekki (2018), and Cassar and Meier (2018) for reviews. This literature has found that meaningful work is related to various benefits in the workplace, such as higher productivity (Ariely et al., 2008; Chadi et al., 2017), reduced turnover (Burbano et al., 2024), fewer absences (Steger et al., 2012), and lower reservation wages (Hu and Hirsh, 2017; Kesternich et al., 2021). But so far, we know little about how to make work meaningful.

Theoretical models identify four main pathways to meaning (Martela and Riekki, 2018; Cassar and Meier, 2018). The first is beneficence, or the feeling of making a positive *social impact* through work by helping other people or society at large. The other three pathways are derived from self-determination theory, which posits that human well-being is rooted in the satisfaction of three basic needs (Ryan and Deci, 2000; Deci and Ryan, 2013). The first is the need for *autonomy*, or a sense of freedom and flexibility over work methods and arrangements. The second is for *competence*, or the perceived ability to apply one's talents, skills, and knowledge on the job. The third is for *relatedness*, or having a connection with colleagues, supervisors, and the workplace or firm. As in Burbano et al. (2024), we will refer to these three components jointly as *non-social impact*.[1]

But how effective are these different pathways at making work meaningful? We address this question by estimating a non-linear, within-individual, production function of work meaning. To do so, we exploit four waves of panel data from the American Working Conditions Survey (AWCS), a representative sample of workers from the United States. The longitudinal nature of these data allows us to overcome concerns related to the idiosyncratic interpretations of the answer-scales, or time-constant differences in productivity and personality traits across individuals, which may determine perceptions of both work meaning and the pathways. The substantial number of questions related to each pathway allows us to use an estimation procedure recently introduced

[1]Throughout this paper, work meaning or any of the pathways capture an individual perception. Two people that work the same job may perceive different levels of social impact or meaning, depending on their idiosyncratic preferences and assessment. We study how *perceived* pathways translate into *perceived* meaning.

by Agostinelli and Wiswall (2025) to deal with measurement error. The benefit of their approach is that we can take into account that the survey questions used to measure work meaning and the different pathways are noisy, have answers that differ in locations and scales, and contain varying information about the underlying latent constructs.

We find that the four-factor production function of Cassar and Meier (2018) explains over half of the variation in meaning *between* and just under half of the variation in meaning *within* individuals. In line with their theoretical model, we estimate that work meaning can be produced through different pathways. However, we highlight substantial heterogeneity in how effective these pathways are. The sense of having a *social impact* has the largest direct output elasticity, at 0.44 in our preferred specification with individual fixed effects and pathway interactions. The effects of *autonomy* and *relatedness* are also sizable, with direct output elasticities of 0.31 and 0.16 respectively. The least effective pathway is *competence*, with a small and imprecisely estimated direct output elasticity of 0.02. We find that ignoring measurement error or individual-specific unobserved heterogeneity meaningfully changes the estimated parameters. The importance of *autonomy* increases substantially when unobserved heterogeneity is not accounted for. This could be because jobs with more autonomy come bundled with disamenities that affect meaning but are omitted in the production function, such as time pressure or isolation, or because individuals with stronger needs for autonomy use stricter evaluation standards.

A second finding is that the different pathways are interconnected in the creation of meaning. Particularly, we estimate negative interactions between social-impact and all dimensions of non-social impact. While these are individually relatively small, the joint total effect is sizable, suggesting that creating meaning through social impact is particularly effective for individuals who perceive their jobs as having little non-social impact. While prior work such as Grant (2008) often emphasizes the synergy between intrinsic and pro-social motivation, our results suggest that increasing perceived social impact is a particularly effective way to make work meaningful when other motivational resources are lacking. This may be of relevance to increase the labor supply of low skilled workers, whose jobs more often lack complexity, autonomy, and skill variety, and who have been slowly leaving the labor market for several decades (Acemoglu and Autor, 2011; Binder and Bound, 2019).

The next step in our analysis is to document heterogeneity in the production function. To do so, we use a clustering approach in the spirit of Bonhomme and Manresa (2015), and classify individuals into a small number of groups based on their production technologies. We find that there are three distinct clusters of individuals. The first are *Self-Reliant Workers*, who derive comparatively more meaning from competence and less from relatedness. They are more likely to be single and male than workers in the other clusters, and make up about a quarter of the sample. The second group are *Community-Oriented Workers*, who primarily create meaning through social impact and relatedness. They are the most likely to have a partner and earn the highest salaries, working mainly in education, health, and management. They are the largest group in our sample and make up about half of the observations. The final cluster are *Multi-Source Workers*, who can create meaning through all pathways.

We then study differences in social and non-social impact across occupations. This allows us to further pinpoint where improvements could be made, and where they could be the most effective. There is a lot of occupational heterogeneity in the fraction of workers that perceives their jobs as having only little social or non-social impact. On one end, we find that many workers in Transportation, Food Preparations and Serving, and Production occupations report low levels of both social and non-social impact. Improving their feelings of social impact would be a particularly effective way to increase their work meaning, which we document as being low. The recent efforts that firms have devoted to building extensive Corporate Social Responsibility programs and crafting intricate Mission Statements could be a step in the right direction (Cassar and Meier, 2018). More directed efforts aimed particularly at these workers may be even more beneficial. On the other hand, in Health Support and Social Service, perceived social impact is high, but non-social impact is low. In these occupations, increasing non-social impact by enhancing feelings of autonomy, competence, and relatedness may be effective. This could be achieved through technological progress making workers better substitutes, as shown in Goldin and Katz (2016).

To interpret the magnitude of these findings, we price work meaning in terms of the equilibrium compensating differential that is paid in the labor market. We find that a standard deviation increase in work meaning is worth around 214 dollars (about 4.7%) of monthly earnings. This is in line with recent willingness-to-pay estimates for the United States, as reported in Maestas et al. (2023). In terms of the pathways, this means that a standard deviation increase in non-social impact – adding up the total effect of the three pathways – is equivalent to about 102 dollars of monthly salary. On the other hand, a standard deviation increase in social impact is valued at about 94 dollars. But the value largely depends on how individuals perceive the non-social impact of their jobs. Those that consider their jobs as having little non-social impact value the increase at almost 121 dollars, whereas those that indicate high non-social impact value the increase at just 67 dollars.

Literature We contribute to the body of work that studies the importance of work meaning (Rosso et al., 2010; Cassar and Meier, 2018; Martela and Riekki, 2018; Burbano et al., 2024). The various beneficial consequences of meaningful work are well documented. This has motivated several papers to study the effectiveness of workplace interventions aimed at changing workers' meaning, through lab, field, and survey experiments (Ariely et al., 2008; Kesternich et al., 2021; Ashraf et al., 2024). These papers have shown that interventions aimed at directly increasing workers' meaning can have substantial effects, and that there is large heterogeneity in workers' responses. On the other hand, several papers document significant cross-sectional correlations between work meaning and the different pathways (Martela and Riekki, 2018; Nikolova and Cnossen, 2020; Burbano et al., 2024; Nikolova et al., 2024). But so far, there is little empirical evidence that studies the relative effectiveness of the different pathways introduced in theoretical models. Yet understanding this is important to identify which interventions could potentially be effective.

A recent paper by Nikolova and Cnossen (2020) has made advances in this direction. They use the European Working Conditions Survey (EWCS), a large and representative sample of European workers, to study how the different non-social impact pathways relate to work meaning. We exploit the panel structure and rich variables of the American Working Conditions Survey (AWCS) to extend their analysis in several ways. First, we address time invariant individual heterogeneity, and estimate a *within*-individual production function. We show that this significantly changes the importance of several pathways to meaning. Second, we model measurement error to address potential attenuation bias using methods based on Cunha and Heckman (2007), Cunha et al. (2010), and Agostinelli and Wiswall (2025). Finally, we simultaneously include all four pathways highlighted in theoretical work. We find that social impact, which is not measured in the

EWCS, has the strongest relation to work meaning. We also highlight the importance of heterogeneity and complementarities in the production process, in line with the theoretical predictions in Cassar and Meier (2018).

We also relate to the literature on compensating differentials for amenities in the workplace (Rosen, 1986; Lavetti, 2023; Bell, 2025). Particularly, we estimate the compensating differential for work meaning in the United States, which we use to price the effectiveness of increasing social- and non-social impact. We find values which are closely aligned with recent worker-side willingness to pay estimates for social impact, reported in Maestas et al. (2023), who use a discrete choice experiment appended to the AWCS. The estimate is also in line with recent estimates on both the compensating differential and workers' willingness to for social impact pay from several European countries reported in Non et al. (2022), Burbano et al. (2024), and De Schouwer and Kesternich (Forthcoming). Several other papers document similar equilibrium prices for particular dimensions of social impact, such as sustainability in Krueger et al. (2023).

Outline. The remainder of this paper is organized as follows. Section 2 presents the production model. Section 3 discusses the empirical strategy and the identification. Section 4 introduces the data and discusses the selection of measures. Section 5 presents the results. Section 6 concludes.

2 The Meaning Production Function

The model builds on theoretical work by Martela and Riekki (2018) and Cassar and Meier (2018), who argue that meaning can be created through both social and non-social impact. The latter is captured by the three psychological needs of Ryan and Deci (2000)'s self determination theory, being autonomy, competence, and relatedness. As proposed in Cassar and Meier (2018), we model an individual's perceived work meaning as a production process, with the different pathways as its inputs. Unlike in their framework we abstract from effort, which aligns closer with models from psychology, such as Rosso et al. (2010) and Martela and Riekki (2018).[2] The within

[2] We do perform a robustness check to assess the importance of effort, to the extent that this can be captured by working hours.

individual production process writes:

$$M_{it} = f_{it}\big(S_{it},\ \underbrace{A_{it}, C_{it}, R_{it},}_{\text{non-social impact}}\ \eta_{it}\big), \tag{1}$$

where M_{it} represents the experienced level of *work meaning* for individual i at time t, S_{it} is their perceived level of *social impact*, and A_{it}, C_{it}, and R_{it} are the perceived levels of the different aspects of *non-social impact*, being *autonomy*, *competence*, and *relatedness*. The final term η_{it} represents an idiosyncratic productivity shock that captures the effects of potentially omitted inputs.

We parameterize the production function as a trans-log process to allow for flexible substitution patterns between the different pathways. An important benefit of this functional form over the commonly used Constant Elasticity of Substitution (CES) functions is that it does not impose prior restrictions on the nature of substitution patterns, see the discussion in Agostinelli and Wiswall (2025). This means that we allow for the social impact component of meaning to be either more, or less, productive at different levels of non-social impact. We assume that the production process f is constant over time, but may vary across individuals of different types $g \in G$. The production function (1) for individuals within a group g rewrites as:

$$\ln M_{it} = \sum_{P \in \mathcal{P}} \gamma_P \ln(P_{it}) + \sum_{P \in \mathcal{P}} \sum_{\substack{P' \in \mathcal{P} \\ P' \neq P}} \gamma_{PP'} \ln(P_{it}) \ln(P'_{it}) + \eta_{it}, \tag{2}$$

where $\mathcal{P} = \{S, A, C, R\}$ denotes the set of pathways. With normalized inputs, the γ_P coefficients represent the direct output elasticity of work meaning with respect to pathway P. The $\gamma_{PP'}$ coefficients on the interaction terms are pair-specific complementarities between pathways P and P'.[3]

3 Empirical Strategy

Measurement Model. Both work meaning and the pathways are difficult concepts to measure. To address this, we follow the literature that estimates human capital production functions, and

[3]Note that $\ln(P_i) \times \ln(P'_i)$ and $\ln(P'_i) \times \ln(P_i)$ are identical, and we include each interaction just once.

introduce a measurement system (Cunha and Heckman, 2007; Cunha et al., 2010; Agostinelli and Wiswall, 2025). Suppose that we have different observed measures for each pathway, and that the latent factors are related to these observed measures through a log-linear measurement model with the following structure[4]:

$$Q_{ijt}^F = \mu_j^F + \lambda_j^F \ln F_{it} + \psi_{ijt}^F \quad \text{for all} \quad F \in \{\mathcal{P} \cup M\}, \tag{3}$$

where Q_{ijt}^F is the j'th measure of the latent factor F at time t for individual i, the measurement parameters μ_j^F and λ_j^F represent the location and scale of the measure, and ψ_{ijt}^F is a measure-specific error term. The error terms are assumed to be mean zero and independent of each other, the latent pathways, and the production shocks η_{it}.

The loading of the first measure of each latent factor (λ_1^F) is normalized to unity without loss of generality. Additionally, we normalize the logarithm of all latent factors $\ln(F)$ to be mean zero. Given these normalizations, we can retrieve the loadings by taking the sample analog of:

$$\lambda_j^F = \frac{\text{Cov}(Q_{ijt}^F, Q_{ij't}^F)}{\text{Cov}(Q_{i1t}^F, Q_{ij't}^F)} \quad \text{for all } j \neq j' \text{ and } F \in \{\mathcal{P} \cup M\}, \tag{4}$$

$$\mu_j^F = \mathbb{E}(Q_{ijt}^F) \quad \text{for all } j \text{ and } F \in \{\mathcal{P} \cup M\}. \tag{5}$$

We then use these estimates to construct the following measures of the latent factors:

$$\ln \tilde{F}_{ijt} = \frac{Q_{ijt}^F - \mu_j^F}{\lambda_j^F} \text{ for all } j \text{ and } F \in \{\mathcal{P} \cup M\},$$

which we use to estimate the production function. Note that for these measures, the following equality holds:

$$\ln F_{ijt} + \frac{\psi_{ijt}^F}{\lambda_j^F} = \frac{Q_{ijt}^F - \mu_j^F}{\lambda_j^F} = \ln \tilde{F}_{ijt}, \text{ for all } F \in \{\mathcal{P} \cup M\}. \tag{6}$$

[4] This assumption is clearly not without loss of generality. But as pointed out in Agostinelli and Wiswall (2025), it is made in most empirical work on human capital production. See Cunha et al. (2021) for an overview of this research. Also note that the latent distributions of each factor can be identified if at least dedicated measures are available, see for example Cunha et al. (2010).

Estimation. We substitute the factors constructed using equation (6) into the production function from Equation (2). After some rewriting (see Appendix A.1 for more details) this yields:

$$\ln \tilde{M}_{ijt} = \sum_{P \in \mathcal{P}} \gamma_P \ln \tilde{P}_{ijt} + \sum_{P \in \mathcal{P}} \sum_{\substack{P' \in \mathcal{P} \\ P' \neq P}} \gamma_{PP'} \ln \tilde{P}_{ijt} \ln \tilde{P}'_{ijt} + \xi_{ijt}(\ln \tilde{P}_{ijt}, \ln \tilde{P}'_{ijt}). \tag{7}$$

The error term (ξ_{ijt}) is correlated with the pathways, so we cannot estimate this equation with ordinary least squares. However, as noted in Agostinelli and Wiswall (2025), alternative measures of the latent pathways that are omitted from the measurement system are valid instruments. They are relevant by definition, and uncorrelated with all components of ξ_{ijt} under the measurement model assumptions. We estimate equation (2) with two stage least square, absorbing individual fixed effects.

Because of the two-step nature of the estimation strategy, consisting of a measurement model and production function, we rely on a bootstrapping procedure for inference. Since we do not want to make an arbitrary choice regarding which measures to include in the measurement model and which to use as instruments, we cycle through all possible choices j to obtain a distribution of estimates.[5] We wrap this entire procedure in a block bootstrap at the individual level, where we draw with replacement the same number of individuals as in our main sample. We report the mean estimates and bootstrapped confidence bands as our main results, but present the entire distributions in Appendix D.

Identification. We rely on within-individual variation in work meaning and the pathways over time to identify the production with individual fixed effects. On the one hand, this addresses concerns related to how respondents differ in interpreting the answer scales. Idiosyncratic assessments of questions and answers could be driven by personal characteristics (such as personality traits), which may be omitted factors in the production function. For example, individuals with stronger needs may use stricter evaluative standards, causing a downward bias in the estimates. This problem is well known in the broader literature on subjective well-being (Ferrer-i Carbonell and Frijters, 2004). On the other hand, this also accounts for issues that are often raised in

[5]After controlling for measurement error, the normalization in equation (4) does not influence the estimation. We therefore do not cycle through that.

the literature on compensating differentials (Rosen, 1986; Lavetti, 2023). Job amenities tend to come bundled, and more productive individuals work jobs that are better in several dimensions (Hamermesh, 1999). Some of these characteristics (e.g., job security) are unobserved, but could be omitted factors in the production function. Controlling for time invariant differences in productivity largely addresses these concerns.

There are several reasons why individuals report different levels of meaning or the pathways over time. Job changes are the most obvious source of variation, yet only a minority of respondents changes their employer (10%) or supervisor (30%) within the sample period (see Appendix B.1). We show in Table A.3 that virtually all (99%) individuals who change jobs report a difference in meaning or any pathway over time. But so do most (62.6%) respondents who do not change employer or supervisor. This variation may be driven by changes in tasks within their existing positions, which affect feelings of competence and autonomy, or variation in the surrounding colleagues, affecting feelings of relatedness. Alternatively, preference shocks may lead individuals to differently assess the same working conditions. See for example Bailey and Madden (2017) and Meng et al. (2023) for a discussion of such temporal dynamics. We exploit all these sources of variation to identify our parameters, and study the importance of potential preference shifters in a heterogeneity analysis.

4 Data

We estimate the model using data from the American Working Conditions Survey (AWCS). The AWCS is collected by Maestas et al. (2023) through the American Life Panel (ALP), a representative survey of workers in the United States, conducted by the RAND Corporation between 2015 and 2018. The questions are modeled after those in the European Working Conditions Surveys (EWCS), with some notable differences. An important benefit of the AWCS is that it contains questions about all pathways, and in four waves of data on the same sample of workers. We construct a panel of all individuals that participated in at least two waves, and end up with almost 5,000 observations for more than 1,600 individuals without any missing values. Summary statistics of our sample can be found Table A.1 in Appendix B.1. We show that, after using the weights constructed by Maestas et al. (2017), the demographic characteristics of our sample align well with those reported in the Current Population Survey (CPS).

Description of the Measures. This subsection discusses the measures we use to capture the latent constructs of *work meaning*, *social impact*, *autonomy*, *competence* and *relatedness*. Table 1 provides an overview of the different measures and how they are questioned. We re-coded all these variables such that higher values indicate higher perceived levels of work meaning or any of the pathways.

Work Meaning. The standard questionnaire used to measure work meaning in psychology is the Work and Meaning Inventory (WAMI), constructed by Steger et al. (2012). The WAMI questionnaire is unfortunately not included in the AWCS. But there are nonetheless several questions that capture meaningful work. The first is a measure of respondents' feelings about doing useful work, the second asks whether a respondent's job provides them with the satisfaction of work well done, and the third asks whether their job provides a sense of personal accomplishment. The first and second questions are used as measures of meaning in Nikolova and Cnossen (2020) and Stephan et al. (2020). Reassuringly, Stephan et al. (2020) show that these measures correlate highly with the WAMI. A measure close to the third has been used as a meaning variable in Cotofan et al. (2023). In a robustness check, we also use a question that asks respondents whether their jobs provide them with goals to aspire to, measured on the same scale as the other questions.

Social Impact. There is a single measure of social impact available in the AWCS, which asks respondents whether their work allows them to make a positive impact on society. Similar questions have been used in Kesternich et al. (2021), Burbano et al. (2024), and De Schouwer and Kesternich (Forthcoming). Note that because we have only a single measure, we do not include social impact in the measurement system. This means that our estimated coefficients could be interpreted as lower bounds, to the extent that they are attenuated by measurement error, although this is difficult to predict due to the non-linearities in the model.

Autonomy. The measures of autonomy in the AWCS capture control over the methods of work and over scheduling. To assess control over work methods, we use questions that ask respondents whether they can apply their own ideas in their work, and if they are involved in improving the organization and processes of their work. The final question captures autonomy

Table 1: Measures of Work Meaning and Pathways

Item	**Description**	**Mean (sd)**
Meaning (M)		
$Q^M_{UsefulWork}$	"You have the feeling of doing useful work". Measured on a five point scale from "Always" to "Never"	2.80 (1.00)
$Q^M_{WorkWellDone}$	"Your job provides satisfaction of work well done". Measured on a five point scale from "Always" to "Never"	2.76 (0.97)
$Q^M_{PersAccomplish}$	"Your job provides you with a sense of personal accomplishment". Measured on a five point scale from "Always" to "Never"	2.70 (1.01)
Social Impact (S)		
$Q^S_{ImpactSociety}$	"Your work allows you to make a positive impact on society". Measured on a five point scale from "Always" to "Never"	2.50 (1.18)
Autonomy (A)		
$Q^A_{ApplyOwnIdeas}$	"You are able to apply your own ideas in your work." Measured on a five point scale from "Always" to "Never"	2.58 (1.07)
$Q^A_{SetSchedule}$	"Can you take breaks when wanted" Measured on a five point scale from "Always" to "Never"	2.53 (1.26)
$Q^A_{OrgInvolvement}$	"You are involved in improving work organization/processes." Measured on a five point scale from "Always" to "Never"	2.30 (1.22)
Competence (C)		
$Q^C_{OpportunityTalents}$	"Your job provides you with opportunities to fully use talents". Measured on a five point scale from "Always" to "Never"	2.50 (1.07)
$Q^C_{SolveProblems}$	"Generally, does your main paid job involve solving unforeseen problems on your own?" Measured by a Yes / No indicator	0.88 (0.38)
$Q^C_{ComplexTasks}$	"Generally, does your main paid job involve complex tasks?" Measured by a Yes / No indicator	0.76 (0.46)
$Q^C_{NewThings}$	"Generally, does your main paid job involve learning new things?" Measured by a Yes / No indicator	0.83 (0.38)
Relatedness (R)		
$Q^R_{ManagementAppreciate}$	"Employees are appreciated when they have done a good job". Measured on a five point scale from "Strongly Agree" to "Strongly Disagree"	2.63 (1.10)
$Q^R_{CooperationColleagues}$	"There is good cooperation between you and your colleagues". Measured on a five point scale from "Strongly Agree" to "Strongly Disagree"	2.99 (0.91)
$Q^R_{ConflictResolution}$	"Conflicts are resolved fairly" Measured on a five point scale from "Strongly Agree" to "Strongly Disagree"	2.59 (1.02)
$Q^R_{LikeRespectColleagues}$	"You like and respect your colleagues". Measured on a five point scale from "Strongly Agree" to "Strongly Disagree"	3.03 (0.84)

Notes. This table provides an overview of the measures of *work meaning*, *social impact*, *autonomy*, *competence*, and *relatedness* in the American Working Conditions Survey (AWCS) available in waves 2015 to 2018. The final column shows the weighted sample means and standard deviations of each measure.

over the work schedule, and asks respondents about their ability to take breaks when they want to. Similar measures are used in Nikolova and Cnossen (2020) and Burbano et al. (2024).

Competence. We use four questions to measure respondents' feelings of competence. The first two measures are the same as those used in Nikolova and Cnossen (2020). These ask respondents about whether they feel like their job involves learning new things and solving unforeseen problems. The third question asks respondents whether their job provides them with opportunities to fully use their talents. The fourth asks respondents whether they feel like their jobs involve complex tasks. These capture an element of competence similar to Burbano et al. (2024), who use a question that asks whether respondents feel like their jobs are too easy.

Relatedness. The measures of relatedness capture whether respondents feel connected to their colleagues and the company. The first set of measures asks respondents whether employees are appreciated when they have done a good job, whether there is good cooperation with colleagues, and whether they like and respect their colleagues. The final question aims to capture more general feelings about the work environment, and asks respondents about their beliefs regarding the resolution of conflicts in the workplace. These questions are again comparable to those used in previous work, such as Nikolova and Cnossen (2020) and Burbano et al. (2024).

Quality. We briefly discuss the distributions of these measures and how they interrelate, more details can be found in Appendix B.2. As highlighted already in Table 1, there is substantial variation in all measures. Social desirability bias does not seem to be a first-order concern, as many respondents answer that they do not feel like their work has a positive impact on society or is useful, with means of 2.50 and 2.79 respectively. This is in line with recent findings of Dur and van Lent (2019). We run an exploratory factor analysis to further explore the information content of the different measures. We do not include work meaning here, because all the pathways should be measures of meaning to some extent. We impose a four factor solution, which is in line with what a scree plot suggests.[6] The exploratory factor model shows that measures are generally informative about the pathway they are assigned to.[7]

[6] A scree plot recommends four to five factors, but the fifth explains significantly less variation.
[7] The main exception is $Q^C_{OpportunityTalents}$, which seems to relate closely with $Q^S_{ImpactSociety}$.

5 Results

Production Function. We now discuss the main production function estimates shown in Table 2. The first two columns present the specifications without individual fixed effects, which respectively do not and do allow for pathway interactions. The final two columns are similar, but for models with individual fixed effects. We find that across all specifications, each pathway enters the production function positively. This highlights that there are several ways to create meaning at work, as suggested in the theoretical models of Cassar and Meier (2018) and Martela and Riekki (2018). Also in line with theory, we find that the model explains a large amount of the variation in work meaning. In our preferred specification with fixed effects and interactions, shown in column (4), the model captures 89% of the variation in meaning between, and 46% of the variation within-individuals.

While all pathways can create meaning, there are substantial differences in their effectiveness. Across all models, social impact has the largest effect. In our preferred specification, we estimate a direct output elasticity of 0.438. The second and third most effective pathways are autonomy and relatedness, with direct output elasticities 0.305 and 0.161 respectively. Competence is the least effective pathway, with a direct output elasticity of 0.023. However, the confidence bounds on this estimate are very wide. This is likely related to measurement issues, as there is little variation in some competence measures due to their binary nature (see Appendix B.2). However, previous work such as Nikolova and Cnossen (2020) also documents a similarly small correlation between meaning and competence.

These results also highlight the importance of accounting for unobserved heterogeneity meaningfully changes the parameter estimates. To assess this effect, we compare our baseline specification to the same model without individual fixed effects, presented in columns (4) and (2) respectively. The effect of social impact decreases by almost 30%, as the point estimate changes from 0.614 to 0.438. The relative change in the effect of autonomy is even larger, with the point estimate more than doubling from 0.136 to 0.305. Changes in the effects of competence and relatedness are smaller. As discussed before, this may be due to idiosyncrasies in the interpretation of answer scales (Ferrer-i Carbonell and Frijters, 2004) or because of other amenities affecting meaning, which we control for by removing time-constant productivity differences, see

Table 2: Production Function Parameters

	(1)	(2)	(3)	(4)
Pathways				
Social Impact	**0.626**	**0.614**	**0.457**	**0.438**
	(0.549, 0.713)	(0.540, 0.693)	(0.353, 0.559)	(0.329, 0.541)
Autonomy	**0.137**	**0.136**	**0.307**	**0.305**
	(0.043, 0.214)	(0.047, 0.208)	(0.102, 0.737)	(0.103, 0.724)
Competence	0.048	0.052	0.023	0.023
	(-0.068, 0.170)	(-0.060, 0.174)	(-0.918, 1.097)	(-0.939, 1.056)
Relatedness	**0.200**	**0.197**	**0.169**	**0.161**
	(0.125, 0.282)	(0.127, 0.278)	(0.081, 0.267)	(0.074, 0.262)
Pathway Interactions				
Social Impact × Autonomy		*-0.059*		-0.057
		(-0.130, 0.006)		(-0.133, 0.021)
Social Impact × Competence		-0.024		-0.029
		(-0.084, 0.035)		(-0.114, 0.050)
Social Impact × Relatedness		-0.017		-0.040
		(-0.086, 0.054)		(-0.098, 0.027)
Autonomy × Competence		0.038		0.004
		(-0.012, 0.094)		(-0.142, 0.171)
Autonomy × Relatedness		0.010		-0.003
		(-0.050, 0.071)		(-0.091, 0.090)
Competence × Relatedness		-0.014		-0.016
		(-0.072, 0.044)		(-0.129, 0.077)
Adjusted R^2	0.578	0.588	0.883	0.888
Within R^2			0.436	0.459
Number of observations	4,858	4,858	4,190	4,190
Individual FE	No	No	Yes	Yes

Notes. Point estimates of the production function parameters – the values of γ_P and $\gamma_{PP'}$ from equation (7) – for specifications with and without interactions, individual, and occupation fixed effects. Below each estimate, we present 95% bootstrapped confidence bounds based on 100 bootstrap samples. Bold faced estimates are significant at the 5% level, italics at 10%. See Appendix C for the complete results.

for example Lavetti (2023). For example, jobs with more autonomy may come bundled with disamenities such as time pressure or isolation, which are omitted in the production function but may reduce meaning.

The next finding from our analysis is that there are interactions between the different pathways, as argued in Cassar and Meier (2018), but that these are individually relatively small. The main pattern is that social impact interacts negatively with all non-social impact variables. The negative interaction is the largest with autonomy (-0.057), followed by relatedness (-0.040) and competence (-0.029). This highlights that social impact could be a particularly efficient source of meaning when perceived non-social impact is lacking, and vice versa. The interactions within the non-social impact pathway, between competence, relatedness, and autonomy themselves, are smaller.

Robustness. We highlight several features related to the robustness of our findings in Appendix D. First, we present the full coefficient distribution from all bootstrapped regressions in Figure A.2. This shows that some results do vary depending on the choice of instrument, and notably the estimates concerning the effect of competence. This highlights the benefits of our agnostic approach that cycles through all potential instrument choices. Second, we do a robustness check related to effort, as discussed in Cassar and Meier (2018) and Nikolova et al. (2024). Table A.8 shows the results from restricting our sample to full-time workers only. The differences in the estimated coefficients are small, with the only exception being the effect of competence, where the point estimate increases substantially. While the error bounds are very wide, the importance of competence and skill usage seems to increase with time spent working.

We also highlight that our estimates are robust to how we measure meaning. Particularly, the meaning measure about useful work could capture some part of social impact. We show in Table A.10 that removing the useful work measure of meaning and replacing it with a question about aspirations yields essentially the same results. We also show that our estimates are robust to including occupation fixed effects in Table A.9. The final robustness check in Table A.11 highlights the importance of accounting for measurement error. As in Agostinelli and Wiswall (2025), we do so by re-running our analysis without instrumenting the pathways. Because of the non-linearities and interrelated equations in the model, there are no clear predictions on the sign of the bias. We do find evidence consistent with attenuation. This is particularly the case for autonomy and relatedness, for which we find that the effects are up to twice as large when addressing measurement error.

5.1 Heterogeneity

Previous work has highlighted substantial heterogeneity in the prevalence of, and preferences for, work meaning across demographic groups (Cassar and Meier, 2018; Kesternich et al., 2021; Burbano et al., 2024; De Schouwer et al., Forthcoming). A potential explanation for these findings is that individuals differ in terms of how they value the different pathways. To study heterogeneity in the production process, we use a grouping method in spirit of Bonhomme and Manresa (2015) and Bonhomme et al. (2022). The idea is that there exist discrete groups, between which we allow the production process to differ.

We implement the estimator in two steps. Similar to Bonhomme and Manresa (2015), the first step consists of summarizing the individual responses into a vector of moments h_i that is informative about the latent groups. These include both the average levels of work meaning and the pathway measures over time, and the within-person correlations between work meaning and the pathways. The first set of moments is informative to the extent that individuals sort jobs with specific characteristics based on how effective these are at making work meaningful. The within-person correlations capture how an individual's meaning moves with the levels of their pathways, separating those who sort into jobs with certain characteristics based on how meaningful these are from other motivations. The second step simply consists of re-estimating the production functions separately within each group to recover the group-specific production function parameters. We discuss our choice regarding the number of groups and the robustness of our results in Appendix A.3.

Results. The results from our heterogeneity analysis are presented in Table 3. To facilitate the interpretation of between-group differences, we estimate the model without the pathway interactions. The table highlights notable heterogeneity in how different workers produce meaning. While in all three clusters social impact is the most important pathway, the relative importance of autonomy, competence, and relatedness differs significantly between groups.

Group I: Self-Reliant Workers. The first group mainly distinguishes itself from the others by deriving a lot of meaning competence ($\gamma_c = 0.178$) and less from relatedness ($\gamma_r = 0.062$). They also value social impact ($\gamma_s = 0.544$) and autonomy ($\gamma_a = 0.115$) averagely. This group creates meaning from using their skills and knowledge, without minding doing so in isolation. They are more likely to be men (59%) and single (47.9%) compared to the other groups. Their level of schooling, age, and salary does not differ substantially from the average. Self-Reliant Workers primarily work in Sales and Transportation occupations, which typically feature less interaction with colleagues. They account for about 27% of the sample.

Group II: Community-Oriented Workers. The second group primarily creates meaning through

Table 3: Production Function Estimates and Demographics by Cluster

Group	I	II	III
Panel A. Production Functions			
Autonomy	0.115	0.062	**0.163**
	(-0.066, 0.254)	(-0.035, 0.158)	(0.072, 0.267)
Competence	0.178	0.011	0.033
	(-0.039, 0.425)	(-0.268, 0.276)	(-0.175, 0.243)
Relatedness	0.062	**0.137**	**0.159**
	(-0.061, 0.178)	(0.059, 0.207)	(0.049, 0.279)
Social Impact	**0.544**	**0.546**	**0.602**
	(0.389, 0.684)	(0.424, 0.649)	(0.477, 0.735)
Adj. R^2	0.395	0.380	0.553
Panel B. Group Characteristics			
Age	43.51	43.51	44.56
Female (%)	41.0	46.2	56.1
Years of Schooling	13.78	14.78	13.65
Has Partner (%p)	52.1	59.4	56.6
Hours/week	40.84	40.45	37.52
Wage	51,390	60,841	37,878
Panel C. Occupations			
Sales	15.4	11.4	8.0
Office and Admin	11.9	6.6	13.8
Bus. and Fin. Ops.	7.7	9.2	10.1
Education	6.7	11.6	7.8
Transportation	13.2	3.4	6.6
Health Support	6.0	8.2	7.7
Production	7.7	1.9	10.4
Management	3.9	8.3	3.5
Food Prep and Serving	3.8	3.6	7.0
Health Pract and Tech	2.0	4.4	4.1
Computer and Math	2.5	6.4	0.5
Comm. and Soc. Serv.	2.1	3.8	2.9
Maintenance	3.0	2.8	2.3
Prot. Serv.	3.1	1.1	3.6
Legal	1.0	3.6	2.3
Clean and Maintenance	2.0	2.2	2.6
Scientist	1.0	2.6	2.4
Pers Care and Serv	2.2	1.3	2.3
Construction	1.3	2.3	1.2
Arch. and Eng.	1.8	2.1	0.1
Observations	959	1,718	855

Notes. Panel A reports standardized elasticities from equation (7) estimated separately by cluster, without interactions. Panel B shows weighted means of demographics by cluster. Panel C highlights occupational heterogeneity across clusters.

social impact ($\gamma_s = 0.546$) and relatedness ($\gamma_r = 0.137$), with autonomy ($\gamma_a = 0.062$) and competence ($\gamma_c = 0.011$) playing a lesser role. They are the highest educated (14.8 years), most likely to have a partner (59.4%), and earn the highest salaries ($60,841 per year). Community-Oriented Workers mainly work in education, health, and management occupations, which emphasize collaboration and shared purpose. They are the largest group in our sample, accounting for 48% of observations.

Group III: Multi-Source Workers. The final group stands out by deriving meaning from several channels. Social impact ($\gamma_s = 0.602$) is the most efficient source of meaning, but relatedness ($\gamma_r = 0.159$) and autonomy ($\gamma_a = 0.163$) can also have a significant effect. This group is distinguished by primarily being women (56%), working the fewest weekly hours (37.5) and having the lowest salaries ($37,878). Multi-Source Workers primarily work in Office, Administration, Business, and Production roles, which all have a relatively high degree of interpersonal connection. They make up about 25% of the sample.

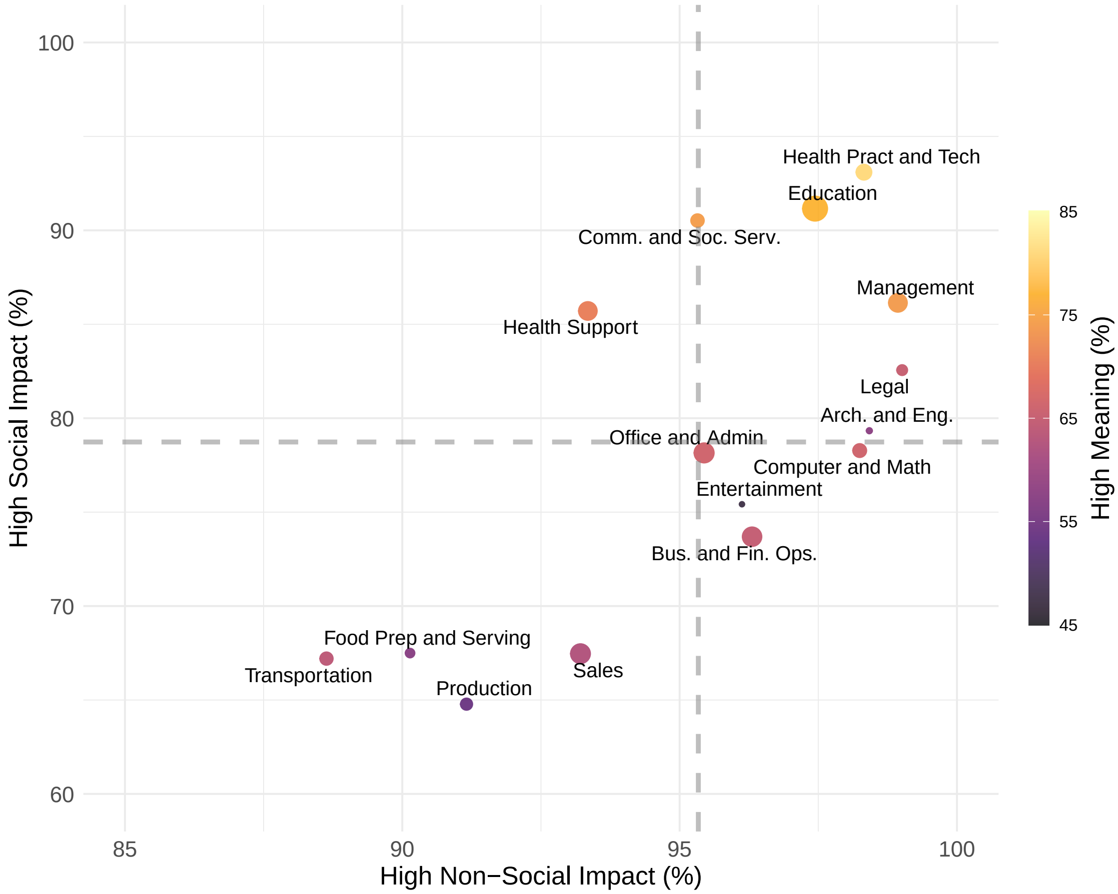
These results reinforce the idea that social impact is the dominant pathway to work meaning for most groups of workers. But they also show that there is significant heterogeneity in the effectiveness of the different non-social impact pathways across demographic groups. There also seems to be some sorting into occupations that align with workers' production technologies.

5.2 Impact Across Occupations

To further assess the importance of occupations, we study differences in meaning, social, and non-social impact. These are highlight in Figure 1. In Production, Transportation, Food Preparation and Serving, and Sales, the fraction of respondents that reports high social (70%) and non-social (90%) impact is the lowest. These are also the occupations where a large fraction of respondents reports that their jobs are not that meaningful, up to almost 50% for Production workers. Based on our findings, increasing the social impact in these jobs could generate substantial benefits for these workers. These results can be related to Dur and van Lent (2019), who find that a high percentage of individuals that work as plant and machine operators, and cooks, waiters or bartenders consider their jobs to be socially useless.

We also find that Health Support and Social Service occupations are characterized by high

Figure 1: Social and Non-Social Impact across Occupations



Notes. This figure highlights the fraction of workers that considers their jobs as having high social and non-social impact, defined as being half of a standard deviation above the mean, across occupations. The grey lines indicate the average levels. Colors indicate the fraction that considers their jobs to have high meaning, also measured as at least half a standard deviation above the mean. The size of each dot indicates the number of people in each occupation in our sample. We show only the fifteen biggest occupations for readability.

social impact but relatively low non-social impact. In these occupations there may be room to further improve non-social impact, which could generate as much as further improving social impact. Technological advances may help raise autonomy, for example by improving control over schedules, as documented for pharmacists by Goldin and Katz (2016). On the other hand, we find that several high-skill occupations, such as those in Business and Law, Computer and Mathematics, and Office and Administration, report high non-social impact, but not always high social impact. Increasing social impact in these occupations will be beneficial, but will not generate as much value as in the group of low non-social impact occupations.

5.3 Money Metric Benefits

The production function estimates provide us with a useful indication for the direction and significance of the different pathways in generating work meaning. To better understand the magnitude of these findings, we translate meaning into monetary terms. We do so by estimating the equilibrium price of work meaning – the *compensating differential* as in Rosen (1986) – and calculate how much dollars a change in social and non-social impact generates.

Pricing Work Meaning. To estimate the equilibrium price of work meaning, we need to address the endogeneity of meaning with respect to wages. The problem is that both meaning and wages are jointly determined by workers' unobserved productivity and their preferences over how to split up their total compensation. More productive workers tend to earn more, but also select into more meaningful jobs. A naive regression of wages on meaning with an imperfect control for productivity thus conflates productive differences with the true compensating differential, as discussed in Hwang et al. (1992).

A recent paper by Bell (2025) provides a novel estimator that addresses this problem.[8] The method relies on an imprecise ability proxy to shift workers' total compensation. Assuming that ability can be captured by a single latent index, we need a proxy variable that is related to productivity but orthogonal to workers' preferences over amenities. General measures of ability, that are not manipulated with the aim of shifting the wage-amenity bundle, satisfy these assumptions. We follow the literature in using years of education as the proxy (Burbano et al., 2024; De Schouwer and Kesternich, Forthcoming).

The estimator can be implemented using a two step approach. The first regresses the ability proxy on both wages and meaning:

$$S_i = \theta_M \ln(M_i) + \theta_W W_i + \xi_i, \tag{8}$$

where S_i denotes years of schooling, M_i the level of meaning derived from our measurement model, and W_i monthly wages. The fitted values from this regression ($\hat{S}_i$) define the direction in

[8] See Folke and Rickne (2022), Burbano et al. (2024), Bell et al. (2024), and De Schouwer and Kesternich (Forthcoming) for recent uses of the estimator.

the (W, M) plane along which productivity increases. The second step uses the constructed productivity control, purged of the measurement error, as a control when tracing out the meaning-wage gradient:

$$W_i = \psi_M \ln(M_i) + \psi_S \hat{S}_i + \epsilon_i. \tag{9}$$

The main coefficient of interest ψ_M captures the compensating differential for meaning along a fixed productivity frontier. We construct standard errors by inverting Anderson-Rubin tests as in Andrews et al. (2019), as suggested by Bell (2025). While these are robust to weak identification, they are generally wider.

Table 4: The Price of Work Meaning (in dollars)

	Base	Productivity Controls	Bell Proxy
Meaning	-23.41 (-99.58 , 52.77)	*-64.90* (-135.18, 5.37)	**-214.40** (-30.53 , -400.08)
Partial F			1024.09

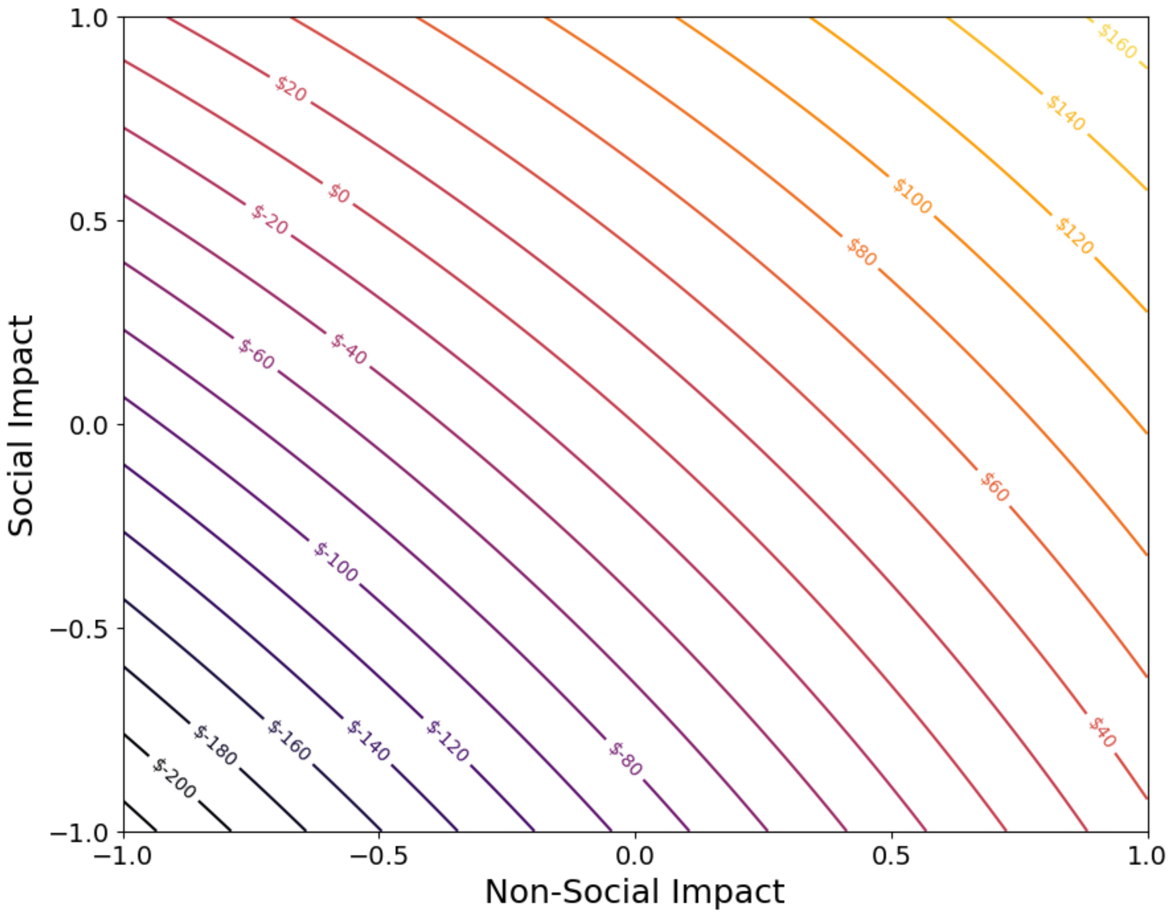
Notes. Coefficients from regressions of meaning on monthly wages. The Base specification contains no control variables, we then introduce productivity controls (years of education), and finally the Bell estimates as discussed in section 5.3. We report 95% confidence intervals, which are derived from T-tests (for the base and productivity specifications) and Anderson-Rubin tests (for the Bell estimates) as discussed in Andrews et al. (2019) and Bell (2025). The Partial F statistic from the first stage regression is presented in the final row. First-Stage results can be found in Appendix C.

The compensating differential estimates are shown in Table 4.[9]. We first estimate a simple linear regression of work meaning on wages without the ability proxy as a control (see Base column). This leads to a small and insignificant estimate of about 20 dollars, confounded by productivity differences. Introducing a noisy ability control (see Productivity Controls column) does little to address this problem, but increases the compensating differential to 65 dollars. The final column (Bell Proxy) presents the estimates from the Bell (2025) estimator described above. We find that the equilibrium price of a standard deviation increase in work meaning is worth almost 220 dollars of monthly wages, or about 4.7%, which is significant at the 95% level.[10] This estimate is broadly in line with the literature. Previous work by Burbano et al. (2024) finds a compensating differential for meaning in Sweden to be between 4 and 5%. Even closer

[9] We show the average across our three measures of meaning, separate estimates are in Appendix C.
[10] Two estimates are significant at the 95% level and one at 90%.

is the estimate by Maestas et al. (2023), who find a willingness to pay for social impact of about 3.6% using a discrete choice experiment within the AWCS. Similar valuations are reported in De Schouwer and Kesternich (Forthcoming) for the Netherlands. These estimates, derived from choice experiments, are significantly more precise.

Figure 2: Money Metric Benefits (monthly salary in $)



Notes. Monetary values, priced in terms of an equilibrium compensating differential in the labor market, for different changes in social and non-social impact. These numbers are based on the production function estimates for our main specification presented in column (4) of Table 2 and the Bell (2025) compensating differential estimate in column (3) of Table 4.

The Monetary Value of Social and Non-Social Impact. We now compute the value generated by a standard deviation change in either social or non-social impact, with the latter summing up the individual effects from autonomy, relatedness, and competence. The result is shown in Figure 2. The curvature of these level lines highlights the degree of substitution between the two dimensions. We find that on average, an increase in social impact is equivalent to a monthly salary increase of about 94 dollars, and an increase in non-social impact is equivalent to about 102 dollars. But despite the individually relatively small substitution effects, the effectiveness of these changes is largely determined by the negative interaction. A standard deviation increase in social impact is twice as effective in creating meaning for individuals that perceive their jobs as having little non-social impact (one standard deviation below the mean), where it is valued at almost 121 dollars, compared to those with high perceived non-social impact (one standard deviation above), where it is valued at just 67 dollars. This suggests that a lot of value can be created by increasing the social impact for workers with only little perceived non-social impact.

These results highlight that increasing social or non-social impact may create substantial value for workers. The question of how this can be achieved naturally arises. Several potential approaches have been proposed in the literature, ranging from concrete workplace interventions to broader policy suggestions. For example, Grant (2007) and Grant et al. (2007) show that contact with beneficiaries may notably increase perceived social impact. Alternatively, Lockwood et al. (2017) and Dur and van Lent (2019) highlight a potential role for government intervention through taxation of harmful or socially useless jobs. In terms of non-social impact, field experiments such as Kelly et al. (2011) highlight how autonomy can be increased by training managers and shifting the workplace policy, see also the review in Spreitzer et al. (2017). Related, expressions of gratitude through direct communications or symbolic awards could be effective ways to increase feelings of relatedness, see for example Grant and Gino (2010) and Kosfeld and Neckermann (2011).

6 Conclusion

This paper studies what makes work meaningful. To do so, we test the model of Cassar and Meier (2018) by estimating a production function with four potential pathways to meaning, being social impact, autonomy, competence, and relatedness. We study how meaning is produced *within* individuals, and allow for measurement error and non-linear effects of the different pathways. The four factor model explains a large share of the variation in meaning between and within individuals. We find that the sense of making a social impact through work is the most effective pathway to meaning, with a direct output elasticity of about 0.44. The different non-social impact pathways jointly have roughly the same effect, with autonomy having the largest direct output elasticity (0.31) followed by relatedness (0.16) and competence (0.02). We also find evidence of a relatively modest negative interaction between social- and each non-social impact pathway, which has a substantial aggregate effect. These estimates are robust to the selection of measures and sample, but addressing unobserved heterogeneity and measurement error is of first order importance.

We then show that there are substantial differences in the production technologies across occupations. Through a clustering algorithm, we identified three groups of workers. The first are *Self-Reliant Workers*, who make up about a quarter of the sample, and derive comparatively more meaning from competence and less from relatedness. They are more likely to be male and single. The second are *Community-Oriented Workers*, who make up about half of the sample, and primarily create meaning through social impact and relatedness. They are the most likely to have a partner and earn the highest salaries, working mainly in education, health, and management. The final cluster of about a quarter of observations are *Multi-Source Workers*, who can create meaning through all pathways.

To interpret the magnitude of these findings, we estimate the compensating differential for work meaning, and use it to price how much value increasing social- and non-social impact could generate. We find that a standard deviation increase in meaning is equivalent to about 4-5% of earnings, which is comparable to recent experimental estimates of workers' willingness to pay. This implies that a standard deviation increase in social impact is equivalent to between $67 and $121 in monthly wages, depending on whether the workers has high or low levels of non-social impact. We show that workers in Transportation, Food Preparation, and Production have the lowest levels of both social and non-social impact. While Health Support workers have relatively high social, but low non-social impact, and the opposite for Business and Financial Operations workers.

These results have several implications. First, they highlight the centrality of social impact as a pathway to meaningful work. The investments that large companies have recently made to develop their mission statements and corporate social responsibility programs could thus be interpreted as an attempt to not only attract customers, but also workers. But in order for these efforts to be effective, they need to be continuous, since we show that workers' perceptions of being engaged in meaningful work or of having a pro-social impact changes significantly over time, even within the same position. Better understanding these dynamics would be an interesting avenue for future research. Given the heterogeneity that we highlight in the production process, tailoring job design to the preferences and characteristics of workers could be the most effective approach to keep work meaningful in the long-term. Yet doing so may require substantial resources from the firm-side. This highlights another interesting avenue for future work. While we briefly discuss some ways of increasing social- and non-social impact that have been studied in the literature, the cost of increasing these pathways likely varies substantially.

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Online Appendix To

What is Meaningful Work?

Thimo De Schouwer Thibault Deneus Marco Forti

A Model and Estimation

A.1 Model Equations

We present the omitted equations from the main text below. Note that substituting the residual measures defined by equation (6) into our production function defined by equation (2) yields:

$$\ln \tilde{M}_{ijt} - \tilde{\psi}^{M}_{ijt} = \sum_{P \in \mathcal{P}} \gamma_P (\ln \tilde{P}_{ijt} - \tilde{\psi}^{P}_{ijt}) + \sum_{P \in \mathcal{P}} \sum_{\substack{P' \in \mathcal{P} \\ P' \neq P}} \gamma_{PP'} (\ln \tilde{P}_{ijt} - \tilde{\psi}^{P}_{ijt})(\ln \tilde{P}'_{ijt} - \tilde{\psi}^{P'}_{ijt}) + \eta_{ijt},$$

where $\tilde{\psi}^{F}_{ijt} = \psi^{F}_{ijt}/\lambda^{F}_{j}$, for $F \in \{\mathcal{P} \cup M\}$. We re-arrange this into equation (7) of the main text, with the equation for the error term (ξ_{ijt}) then being defined by:

$$\xi_{ijt} = \eta_{ijt} + \tilde{\psi}^{M}_{ijt} - \Big[\sum_{P \in \mathcal{P}} \gamma_P \tilde{\psi}^{P}_{ijt} \Big] + \sum_{P \in \mathcal{P}} \sum_{\substack{P' \in \mathcal{P} \\ P' \neq P}} \gamma_{PP'} \Big[\tilde{\psi}^{P}_{ijt} \tilde{\psi}^{P'}_{ijt} - \ln \tilde{P}_{ijt} \tilde{\psi}^{P}_{ijt} - \ln \tilde{P}'_{ijt} \tilde{\psi}^{P}_{ijt} \Big]. \tag{10}$$

A.2 Estimation Procedure

The first-stage regressions we run are of the form:

$$\ln \tilde{F}_{ijt} = \beta^{F}_{j} Q^{F}_{ijt} + \nu_{ijt} \text{ for all } F \in \{\mathcal{P} \cup M\} \text{ and with } j \neq k. \tag{11}$$

We use this to predict $\ln \hat{F}$, which is the factor cleansed of measurement error. The production function that we estimate is:

$$\ln \hat{M}_{ijt} = \sum_{P \in \mathcal{P}} \gamma_P \ln \hat{P}_{ijt} + \sum_{P \in \mathcal{P}} \sum_{\substack{P' \in \mathcal{P} \\ P' \neq P}} \gamma_{PP'} \left(\ln \hat{P}_{ijt} \times \ln \hat{P}'_{ijt} \right) + \epsilon_{ijt}, \tag{12}$$

where ϵ_{ijt} is uncorrelated with the pathways. Some specifications in the main text include fixed effects in these regressions.

A.3 Heterogeneity Analysis

This appendix provides further details on the two-step K-means clustering method in spirit of Bonhomme and Manresa (2015) that we apply for the heterogeneity analysis. As explained in the main text, we implement the estimator in two steps. Similar to Bonhomme and Manresa (2015), we first summarize responses into a vector of moments h_i that is informative about the latent groups. These include both the average levels of work meaning and the pathway measures over time, and the within-person correlations between work meaning and the pathways. The second step simply consists of re-estimating the measurement system and production functions separately within each group to recover group-specific parameters.

Cluster Selection. To determine the number of latent groups, we explored several commonly used criteria. The method proposed by Bonhomme et al. (2022) selects the smallest number of clusters K such that the mean squared distance of individuals from their assigned group center, denoted $\hat{Q}(K)$, is below an estimate of the sampling variability of the individual moments, denoted $\hat{V}_h$. The idea is to add groups only if they help explain systematic differences across individuals, rather than pick up noise.

However, we found that this did not select a parsimonious number of groups in our data. Even for $K = 25$, $\hat{Q}(K)$ remains larger than $\hat{V}_h$ when using the recommended value $\gamma = 1$. But this failure is informative, as it primarily arises because our moments are constructed from noisy variable in a short panel (2 to 4 periods), so $\hat{V}_h$ is relatively small. At the same time, the dispersion in observed individual profiles remains large, keeping $\hat{Q}(K)$ above the noise threshold.

We therefore rely on some alternative widely used diagnostic criteria. First, the "elbow rule" inspects the sequence of fit values $\hat{Q}(K)$. For small K, adding an additional cluster sharply reduces $\hat{Q}(K)$, but after a certain point, further reductions are marginal. The elbow of the curve, where the rate of improvement flattens, in our data occurs at $K = 3$. Second, "silhouette scores" measure how distinct the clusters are, also maximized at low K, and indicate that three clusters provide a reasonable separation. Finally, stability checks using repeated sub-samples and multiple random starts show high adjusted Rand indices (average ARI $= 0.82$), confirming that the three-way partition is robust.

Taken together, these diagnostics support the use of $K = 3$ latent groups. The within-group co-clustering probability (0.775) is much higher than the between-group probability (0.119), yielding a large separation index (0.656). This suggests that the three groups capture economically meaningful and stable heterogeneity in the data.

B Summary Statistics and Exploratory Analysis

B.1 Sample Summary Statistics

Table A.1 compares the main demographics in our sample to those found in the Current Population Survey for 2015. We use the sample weights constructed by Maestas et al. (2017). We find that our sample is generally representative in terms of demographics, as ages, gender, and education levels line up well. We also find that the labor market outcomes are close in terms of both the hours worked and earnings reported in the Current Population Survey.

Table A.1: Sample Summary Statistics.

	CPS	AWCS
Demographics		
Fraction Age 25–34	23.2	22.3
Fraction Age 35–49	32.7	27.0
Fraction Female	51.4	47.0
Fraction High School or Less	37.6	33.9
Fraction Some College or Associate's	28.2	28.4
Fraction BA+	34.2	37.7
Labor Market		
Fraction Part-Time (hours < 35)	14.8	16.5
Average Weekly Hours (main job)	39.8	40.0
Average Weekly Hours (all jobs)	39.7	40.0
Median Monthly Earnings (main job, in k$)	3.33	3.67
Average Monthly Earnings (main job, in k$)	4.41	4.4
Average # Waves (unweighted)		3.06
Number of Individuals		1,588
Share with Same Employer (%)		89.02
Share with Same Boss (%)		72.15

Notes. This table presents the summary statistics for our sample, and compares them to demographics from the Current Population Survey as reported in Maestas et al. (2017).

B.2 Measures: Quality, Variation, and Interrelation

This Appendix first discusses the distribution of measures, then shows how these vary within individuals, and finally presents the results from an Exploratory Factor Analysis (EFA).

Table A.2: Distributions of the Measures.

	Mean	Std. Dev.	10%	25%	50%	75%	90%
Work Meaning (M)							
$Q^M_{UsefulWork}$	2.80	1.00	2.00	2.00	3.00	4.00	4.00
$Q^M_{WorkWellDone}$	2.76	0.97	2.00	2.00	3.00	3.00	4.00
$Q^M_{PersAccomplish}$	2.70	1.01	1.00	2.00	3.00	3.00	4.00
Social Impact (S)							
$Q^S_{ImpactSociety}$	2.50	1.18	1.00	2.00	3.00	3.00	4.00
Autonomy (A)							
$Q^A_{ApplyOwnIdeas}$	2.58	1.07	1.00	2.00	3.00	3.00	4.00
$Q^A_{SetSchedule}$	2.53	1.26	0.70	2.00	3.00	4.00	4.00
$Q^A_{OrgInvolvement}$	2.30	1.22	0.00	2.00	2.00	3.00	4.00
Competence (C)							
$Q^C_{OpportunityTalents}$	2.50	1.07	1.00	2.00	3.00	3.00	4.00
$Q^C_{SolveProblems}$	0.88	0.38	0.00	1.00	1.00	1.00	1.00
$Q^C_{ComplexTasks}$	0.76	0.46	0.00	0.00	1.00	1.00	1.00
$Q^C_{NewThings}$	0.83	0.38	0.00	1.00	1.00	1.00	1.00
Relatedness (R)							
$Q^R_{ManagementAppreciate}$	2.63	1.10	1.00	2.00	3.00	3.00	4.00
$Q^R_{CooperationColleagues}$	2.99	0.91	2.00	3.00	3.00	4.00	4.00
$Q^R_{ConflictResolution}$	2.59	1.02	1.00	2.00	3.00	3.00	4.00
$Q^R_{LikeRespectColleagues}$	3.03	0.84	2.00	3.00	3.00	4.00	4.00

Notes. Distribution of the different measures of work meaning, social impact, autonomy, competence, and relatedness in the American Working Conditions Survey (AWCS).

The distributions of the measures are shown in Table A.2. The main takeaway is that we generally have a substantial amount of variation in all of these measures. Even variables that capture the usefulness of individuals' jobs, where the standard deviation is about one. A substantial fraction of more than 25% of respondents indicates rather low levels of usefulness. The same pattern shows for the measures of impact on society. We find that the fraction of individuals reporting only a minimal positive impact on society is more than 10%. The variation in these measures is important, and addresses the concern that individuals (report) finding their own work extremely useful and beneficial. It also suggests that socially desirable answers are not a very large problem. As expected, we find the lowest variance for the binary measures. For example, whether an individual learns new things or perceives their job as featuring solving complex tasks, where we find that 83% and 76% of individuals respectively respond affirmatively.

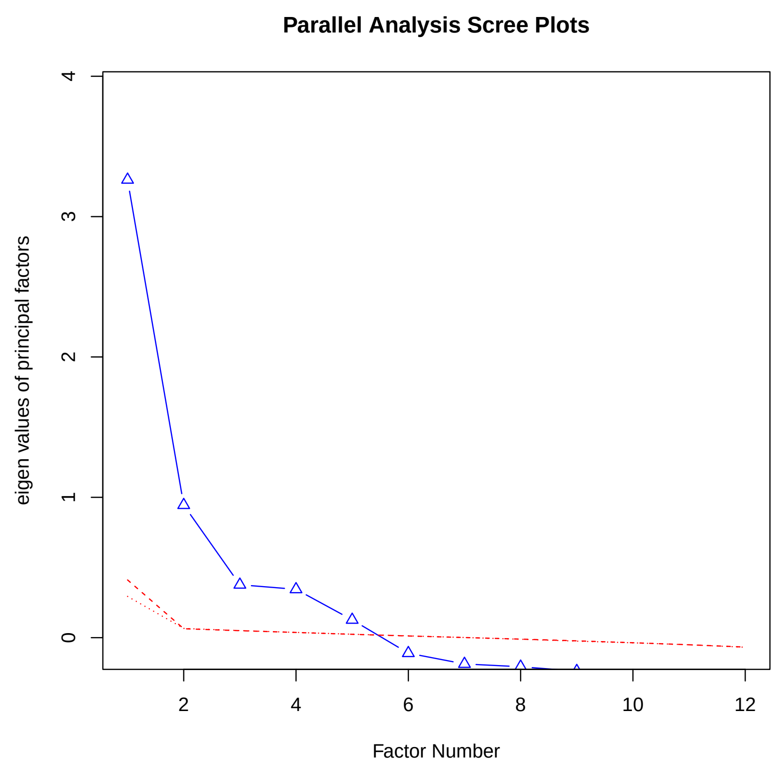
Table A.3: Within-Person Variation of the Measures.

	% Changers	% Changers Different Job	% Changers Same Job	Within-person SD
Work Meaning (M)	61.4%	75.5%	46.0%	
$Q^M_{UsefulWork}$	44.1%	55.2%	32.6%	0.39
$Q^M_{WorkWellDone}$	44.7%	57.0%	31.6%	0.38
$Q^M_{PersAccomplish}$	49.5%	61.5%	36.0%	0.43
Social Impact (S)	50.2%	64.1%	35.7%	
$Q^S_{ImpactSociety}$	50.2%	64.1%	35.7%	0.46
Autonomy (A)	70.0%	85.6%	51.7%	
$Q^A_{ApplyOwnIdeas}$	48.9%	62.4%	32.7%	0.41
$Q^A_{SetSchedule}$	47.6%	57.6%	34.0%	0.42
$Q^A_{OrgInvolvement}$	52.7%	66.9%	36.4%	0.51
Competence (C)	59.8%	73.5%	44.3%	
$Q^C_{OpportunityTalents}$	45.7%	57.3%	33.1%	0.40
$Q^C_{SolveProblems}$	16.1%	20.5%	10.8%	0.10
$Q^C_{ComplexTasks}$	23.6%	29.9%	15.4%	0.15
$Q^C_{NewThings}$	16.8%	22.4%	10.0%	0.10
Relatedness (R)	71.0%	92.3%	47.7%	
$Q^R_{ManagementAppreciate}$	52.2%	72.0%	30.3%	0.46
$Q^R_{CooperationColleagues}$	43.4%	57.9%	27.1%	0.34
$Q^R_{ConflictResolution}$	52.7%	72.6%	30.9%	0.46
$Q^R_{LikeRespectColleagues}$	45.6%	65.6%	23.5%	0.36
Any measure changed	81.8%	99.0%	62.6%	

Notes. Fraction of individuals reporting different values for the measures of work meaning, social impact, autonomy, competence, and relatedness, as well as the within-person standard deviation in the American Working Conditions Survey (AWCS).

Table A.3 highlights that there is substantial within-person variation in most of our measures. Particularly, job changes are a notable source of variation in meaning and all pathways, with almost all respondents who change jobs reporting a difference in at least one measure. We see the largest change in relatedness, with over 90% of respondents indicating different levels of relatedness in their new positions. But we also observe a substantial amount of variation for those that do not change jobs, indicating that peoples' perceptions about their jobs are far from static. More than 60% of respondents report changes in meaning or any of the pathways. These percentage of people indicating a change is relatively similar across measures and pathways.

Figure A.1: Exploratory Factor Analysis – Scree Plot



Notes. Scree plot of an Exploratory Factor Analysis to study the interrelation of the different measures of work meaning, social impact, autonomy, competence, and relatedness in the American Working Conditions Survey (AWCS).

To explore how the different measures are interrelated, we show the results from an Exploratory Factor Analysis in Table A.4. We imposed a four factor solution, in line with the theoretical model of Cassar and Meier (2018). This is generally supported by the scree plot in Figure A.1. A fifth factor could be added but would explain little additional variation. We find that the first factor captures relatedness, with all measures that we labeled as capturing relatedness having loadings between 0.5 and 0.9. The third factor captures autonomy, with all measures loading between 0.050 and 0.85. The fourth factor captures competence. Only the second factor seems to have an ambiguous interpretation, because both our social impact measure and the competence measure that assesses opportunities to use talents load highly. This is important to take into account when we looking at our dedicated measurement system.

Table A.4: Exploratory Factor Analysis – Results

	Factor 1	Factor 2	Factor 3	Factor 4
Social Impact (S)				
$Q^{S}_{ImpactSociety}$	-0.002	**0.800**	-0.049	-0.033
Autonomy (A)				
$Q^{A}_{ApplyOwnIdeas}$	-0.057	0.044	**0.845**	-0.024
$Q^{A}_{SetSchedule}$	0.011	-0.091	**0.565**	-0.029
$Q^{A}_{OrgInvolvement}$	0.021	0.071	**0.618**	0.057
Competence (C)				
$Q^{C}_{OpportunityTalents}$	-0.036	**0.873**	0.002	0.011
$Q^{C}_{SolveProblems}$	-0.004	-0.079	0.029	**0.512**
$Q^{C}_{ComplexTasks}$	-0.016	-0.016	-0.091	**0.738**
$Q^{C}_{NewThings}$	0.024	0.118	0.042	**0.371**
Relatedness (R)				
$Q^{R}_{ManagementAppreciate}$	**0.514**	0.222	0.052	-0.056
$Q^{R}_{CooperationColleagues}$	**0.907**	-0.136	-0.016	0.038
$Q^{R}_{ConflictResolution}$	**0.652**	0.100	0.009	-0.021
$Q^{R}_{LikeRespectColleagues}$	**0.854**	-0.090	-0.037	0.017

Notes. Exploratory Factor Analysis to study the interrelation of the different measures of work meaning, social impact, autonomy, competence, and relatedness in the American Working Conditions Survey (AWCS). Values greater than 0.50 in bold font.

C Results

C.1 Measurement System Estimates

We now look at the results of estimating the dedicated measurement system in Table A.5. This shows that all measures load in the expected direction, and that the weights for the different measures are relatively comparable. This means that the information content about the latent pathways is similar for all measures. We find no indication that the competence measure about opportunities to use talents measures something entirely different than the other measures of competence.

Table A.5: Measurement System Estimates.

	weights	intercepts
Work Meaning (M)		
$Q^M_{UsefulWork}$	1.000	2.796
$Q^M_{WorkWellDone}$	1.001	2.758
$Q^M_{PersAccomplish}$	1.053	2.704
Social Impact (S)		
$Q^S_{ImpactSociety}$	1.000	2.498
Autonomy (A)		
$Q^A_{ApplyOwnIdeas}$	1.000	2.577
$Q^A_{SetSchedule}$	0.718	2.534
$Q^A_{OrgInvolvement}$	0.918	2.302
Competence (C)		
$Q^C_{OpportunityTalents}$	1.000	2.502
$Q^C_{SolveProblems}$	0.533	0.878
$Q^C_{ComplexTasks}$	1.083	0.757
$Q^C_{NewThings}$	0.878	0.829
Relatedness (R)		
$Q^R_{ManagementAppreciate}$	1.000	2.628
$Q^R_{CooperationColleagues}$	0.947	2.986
$Q^R_{ConflictResolution}$	1.054	2.591
$Q^R_{LikeRespectColleagues}$	0.828	3.031

Notes. Results from estimating the measurement system in equations (4) and (5). using data from the American Working Conditions Survey (AWCS).

C.2 The Bell Estimator

This Appendix presents the first-stage results from the estimator of Bell (2025) discussed in section 5.3 and then shows the estimates for our different measures of meaning. As mentioned in the main text, we use years of education as the productivity proxy. To price the amenities, we Winsorized the wage distribution at the top and bottom 5%. We ran the regressions on all waves combined.

Table A.6: First Stage Results.

Outcome: Years of Education	$Q^M_{UsefulWork}$	$Q^M_{WorkWellDone}$	$Q^M_{PersAccomplish}$
Work Meaning	0.03	**0.09**	**0.05**
	(0.03)	(0.03)	(0.02)
Monthly Wages (in 1.000$)	**0.27**	**0.27**	**0.27**
	(0.01)	(0.01)	(0.01)
Cons.	**14.02**	**14.01**	**14.02**
	(0.21)	(0.21)	(0.21)
R^2	0.47	0.47	0.47
Adj. R^2	0.47	0.47	0.47
Num. obs.	4,770	4,770	4,770

Notes. First stage regression of Bell (2025) estimator outlined in section 5.3. Standard errors in parentheses. Bold-faced estimates are significant at the 5% level. Wages are expressed in thousand dollar per month. Data is from the American Working Conditions Survey (AWCS).

The first stage results are sown in Table A.6. While these have no structural interpretation, positive signs on the coefficients reflect that these are forms of compensation that workers enjoy, as discussed in Bell (2025). We find this to be the case for work meaning and wages for all the different measures.

Table A.7 shows the compensating differentials estimates. We find that, across the different measures of meaning, the compensating differentials have the expected sign but differ in magnitude. We find the lowest value of 105 dollars of monthly salary for the question about doing useful work. The highest amount is associated with feelings of work well done, at 335 dollars per month. We average across these values in the main text.

Table A.7: Compensating Differentials Estimates

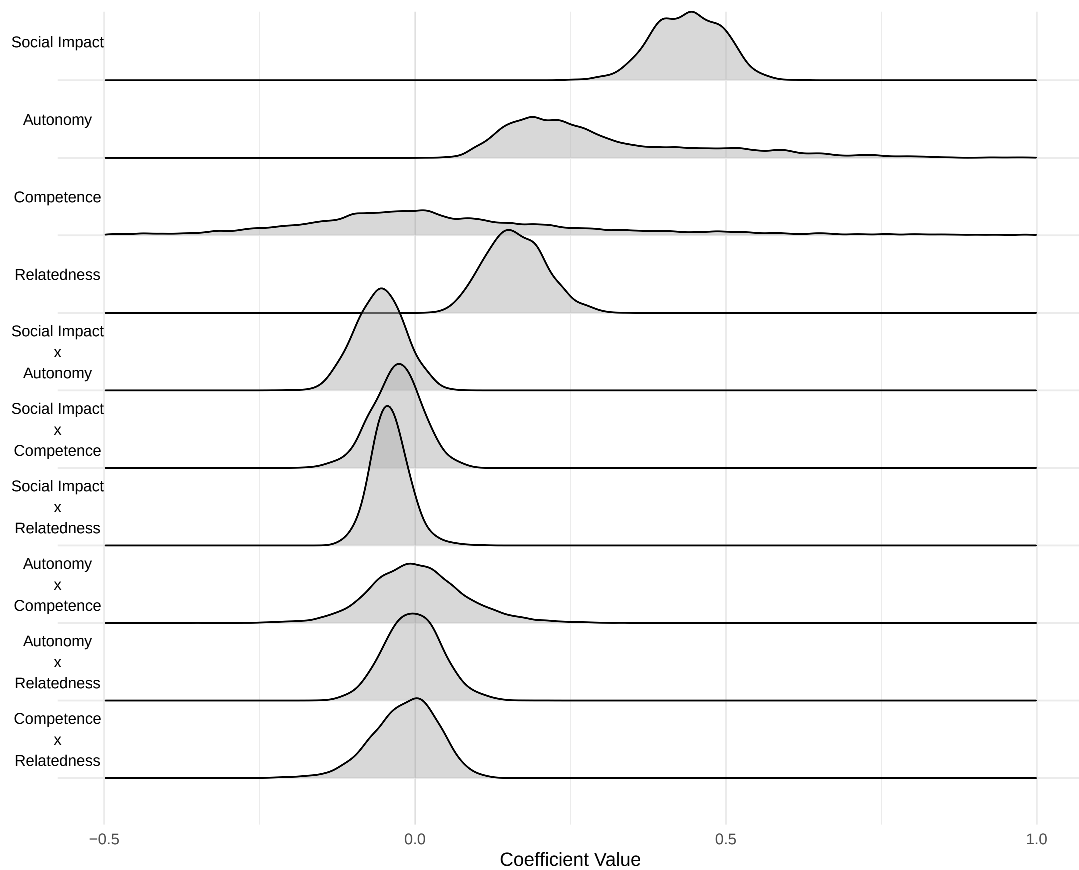
	Base	Productivity Controls	Bell Proxy	Partial F
Meaning Well Done	-72.95 (-149.76 , 3.87)	-111.55 (-182.54 , -40.55)	-335.09 (-150.18 , -522.47)	1023.63
Meaning Useful	-16.22 (-93.87 , 61.44)	-69.75 (-141.11 , 1.61)	-105.70 (82.00 , -294.26)	1027.36
Meaning Accomplish	18.94 (-55.12 , 93.00)	-13.41 (-81.89 , 55.07)	-202.40 (-23.40 , -383.51)	1021.28

Notes. This table shows the results from estimating the compensating differentials using wage regressions and the estimator by Bell (2025) outlined in section 5.3. Data is from the American Working Conditions Survey (AWCS).

D Robustness Checks

This appendix discusses the robustness of our estimates. We first show the entire distribution of the estimated parameters in Figure A.2. We then check whether the estimates are similar in a sample of full-time workers only in Table A.8. Finally, we look at how measurement error influences our results by estimating the model without measurement error correction in Table A.11.

Figure A.2: Distribution of the Production Function Parameters



Notes. Distribution of coefficient estimates – the values of γ_P and $\gamma_{PP'}$ from equation (7) – from our main specification. Based on 100 bootstraps that cycle through all specifications. Data from the American Working Conditions Survey (AWCS).

Table A.8: Production Function Parameters – Full Time

	(1)	(2)	(3)	(4)
Social Impact	**0.627**	**0.615**	**0.471**	**0.450**
	(0.540, 0.727)	(0.533, 0.708)	(0.348, 0.587)	(0.330, 0.554)
Autonomy	**0.142**	**0.142**	**0.291**	**0.284**
	(0.033, 0.235)	(0.038, 0.233)	(0.073, 0.706)	(0.059, 0.705)
Competence	0.048	0.051	0.317	0.326
	(-0.060, 0.171)	(-0.051, 0.179)	(-0.239, 1.706)	(-0.222, 1.745)
Relatedness	**0.204**	**0.200**	**0.155**	**0.147**
	(0.122, 0.297)	(0.126, 0.292)	(0.057, 0.268)	(0.051, 0.253)
Social Impact $\times$ Autonomy		-0.062		-0.057
		(-0.137, 0.020)		(-0.131, 0.032)
Social Impact $\times$ Competence		-0.024		-0.050
		(-0.097, 0.037)		(-0.136, 0.044)
Social Impact $\times$ Relatedness		-0.025		-0.032
		(-0.100, 0.054)		(-0.098, 0.045)
Autonomy $\times$ Competence		0.036		0.005
		(-0.018, 0.097)		(-0.172, 0.198)
Autonomy $\times$ Relatedness		0.015		-0.015
		(-0.065, 0.090)		(-0.107, 0.072)
Competence $\times$ Relatedness		-0.006		0.003
		(-0.074, 0.055)		(-0.109, 0.110)
Adjusted R^2	**0.582**	**0.594**	**0.890**	**0.895**
	(0.499, 0.654)	(0.509, 0.669)	(0.852, 0.921)	(0.860, 0.925)
Within R^2			**0.427**	**0.453**
			(0.340, 0.513)	(0.362, 0.539)
Number of observations	3,906	3,906	3,329	3,329
Individual FE	No	No	Yes	Yes
Occupation FE	No	No	No	No

Notes. Point estimates of the production function parameters – the values of γ_P and $\gamma_{PP'}$ from equation (7) – for specifications with and without interactions, individual, and occupation fixed effects. Below each estimate, we present 95% bootstrapped confidence bounds based on 100 bootstrap samples. Bold faced estimates are significant at the 5% level. Full time workers only.

Table A.9: Production Function Parameters – With Occupation Fixed Effects

	(1)	(2)	(3)	(4)
Social Impact	**0.613**	**0.601**	**0.456**	**0.433**
	(0.530, 0.693)	(0.523, 0.680)	(0.348, 0.555)	(0.324, 0.534)
Autonomy	**0.170**	**0.171**	**0.323**	**0.322**
	(0.062, 0.264)	(0.065, 0.265)	(0.101, 0.788)	(0.106, 0.776)
Competence	0.052	0.060	-0.034	-0.037
	(-0.079, 0.176)	(-0.065, 0.187)	(-0.918, 0.816)	(-0.932, 0.768)
Relatedness	**0.205**	**0.196**	**0.168**	**0.161**
	(0.128, 0.289)	(0.124, 0.274)	(0.080, 0.271)	(0.073, 0.265)
Social Impact $\times$ Autonomy		-0.051		-0.059
		(-0.120, 0.015)		(-0.137, 0.022)
Social Impact $\times$ Competence		-0.007		-0.034
		(-0.073, 0.070)		(-0.117, 0.044)
Social Impact $\times$ Relatedness		-0.019		-0.048
		(-0.078, 0.045)		(-0.102, 0.012)
Autonomy $\times$ Competence		0.034		0.002
		(-0.026, 0.091)		(-0.123, 0.122)
Autonomy $\times$ Relatedness		-0.004		-0.000
		(-0.065, 0.058)		(-0.084, 0.088)
Competence $\times$ Relatedness		-0.016		-0.008
		(-0.082, 0.045)		(-0.117, 0.085)
Adjusted R^2	**0.610**	**0.619**	**0.888**	**0.893**
	(0.549, 0.672)	(0.557, 0.680)	(0.853, 0.936)	(0.858, 0.941)
Within R^2	**0.569**	**0.579**	**0.423**	**0.447**
	(0.497, 0.628)	(0.506, 0.638)	(0.330, 0.507)	(0.356, 0.539)
Number of observations	4,858	4,858	4,190	4,190
Individual FE	No	No	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes

Notes. Point estimates of the production function parameters – the values of γ_P and $\gamma_{PP'}$ from equation (7) – for specifications with and without interactions, individual, and occupation fixed effects. Below each estimate, we present 95% bootstrapped confidence bounds based on 100 bootstrap samples. Bold faced estimates are significant at the 5% level. No measurement error corrections.

Table A.10: Production Function Parameters – Alternative Measure

	(1)	(2)	(3)	(4)
Social Impact	**0.622**	**0.611**	**0.433**	**0.418**
	(0.547, 0.710)	(0.536, 0.695)	(0.314, 0.546)	(0.298, 0.532)
Autonomy	**0.139**	**0.140**	**0.273**	**0.272**
	(0.046, 0.211)	(0.052, 0.208)	(0.081, 0.660)	(0.084, 0.662)
Competence	0.079	0.086	0.134	0.132
	(-0.037, 0.211)	(-0.033, 0.219)	(-0.562, 1.301)	(-0.581, 1.317)
Relatedness	**0.203**	**0.201**	**0.166**	**0.156**
	(0.127, 0.283)	(0.128, 0.280)	(0.079, 0.260)	(0.071, 0.250)
Social Impact × Autonomy		-0.053		-0.058
		(-0.126, 0.023)		(-0.138, 0.026)
Social Impact × Competence		-0.019		-0.020
		(-0.080, 0.040)		(-0.102, 0.055)
Social Impact × Relatedness		-0.011		-0.032
		(-0.073, 0.053)		(-0.086, 0.023)
Autonomy × Competence		0.041		-0.003
		(-0.011, 0.096)		(-0.140, 0.141)
Autonomy × Relatedness		0.003		-0.009
		(-0.048, 0.065)		(-0.089, 0.077)
Competence × Relatedness		-0.010		-0.012
		(-0.077, 0.053)		(-0.118, 0.072)
Adjusted R^2	**0.584**	**0.592**	**0.897**	**0.901**
	(0.512, 0.648)	(0.521, 0.657)	(0.859, 0.938)	(0.864, 0.941)
Within R^2			**0.442**	**0.465**
			(0.351, 0.529)	(0.370, 0.559)
Number of observations	4,836	4,836	4,163	4,163
Individual FE	No	No	Yes	Yes
Occupation FE	No	No	No	No

Notes. Point estimates of the production function parameters – the values of γ_P and $\gamma_{PP'}$ from equation (7) – for specifications with and without interactions, individual, and occupation fixed effects. Below each estimate, we present 95% bootstrapped confidence bounds based on 100 bootstrap samples. Bold faced estimates are significant at the 5% level. No measurement error corrections.

Table A.11: Production Function Parameters – No Measurement Correction

	(1)	(2)	(3)	(4)
Social Impact	**0.562**	**0.554**	**0.525**	**0.503**
	(0.304, 0.709)	(0.308, 0.696)	(0.247, 0.702)	(0.241, 0.678)
Autonomy	**0.100**	**0.098**	0.090	0.085
	(0.003, 0.206)	(0.004, 0.199)	(-0.059, 0.218)	(-0.056, 0.205)
Competence	0.113	0.109	0.096	0.091
	(-0.071, 0.539)	(-0.073, 0.528)	(-0.101, 0.510)	(-0.104, 0.504)
Relatedness	**0.147**	**0.145**	**0.094**	**0.089**
	(0.022, 0.277)	(0.037, 0.275)	(0.002, 0.189)	(0.005, 0.179)
Social Impact $\times$ Autonomy		-0.042		-0.056
		(-0.126, 0.044)		(-0.172, 0.059)
Social Impact $\times$ Competence		-0.016		-0.040
		(-0.093, 0.061)		(-0.173, 0.068)
Social Impact $\times$ Relatedness		-0.014		-0.040
		(-0.091, 0.071)		(-0.118, 0.043)
Autonomy $\times$ Competence		0.008		0.004
		(-0.067, 0.080)		(-0.094, 0.108)
Autonomy $\times$ Relatedness		0.005		0.008
		(-0.069, 0.074)		(-0.089, 0.100)
Competence $\times$ Relatedness		0.001		0.003
		(-0.093, 0.087)		(-0.079, 0.098)
Adjusted R^2	**0.547**	**0.557**	**0.788**	**0.797**
	(0.443, 0.663)	(0.454, 0.674)	(0.732, 0.848)	(0.744, 0.855)
Within R^2			**0.404**	**0.429**
			(0.274, 0.532)	(0.302, 0.563)
Number of observations	4,858	4,858	4,190	4,190
Individual FE	No	No	Yes	Yes
Occupation FE	No	No	No	No

Notes. Point estimates of the production function parameters – the values of γ_P and $\gamma_{PP'}$ from equation (7) – for specifications with and without interactions, individual, and occupation fixed effects. Below each estimate, we present 95% bootstrapped confidence bounds based on 100 bootstrap samples. Bold faced estimates are significant at the 5% level. No measurement error corrections.